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Optimization of FDM 3D printing process parameters for multi-material using artificial neural network

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ABSTRACT

The Additive Manufacturing technology initially developed as a visualization and validation tool. The recent advancement in this technology like Fused Deposition Modeling (FDM), Stereolithography (SLA) and Selective Laser Sintering (SLS) make it rapid manufacturing. However, the manufacturing of ready to use parts using FDM is a challenging task. The processing parameters like infill density, infill pattern, extrusion temperature affect the design, quality, functionality and mechanical properties of the final part vigorously. The present article discusses the effects of material density, infill density and extrusion temperature on tensile strength of Acrylonitrile Butadiene Styrene (ABS), Polyethylene Terephthalate Glycol (PETG), and Multi-material test pieces. Multi-material is fabricated by merging 50% of ABS and 50% of PETG layer by layer in FDM 3D Printing. A total of 30 test pieces as per the ASTM D638-(IV) standard was printed having different infill density, extrusion temperature, and material density. In addition to this, Infill density and extrusion temperature are optimized for increasing the tensile strength of FDM fabricated units. Artificial neural network (ANN) and genetic algorithm-artificial neural network (GA-ANN) hybrid tool in MATLAB-16.0 are used for training and optimization purposes. It is observed that GA-ANN has maximized the tensile strength up to 4.54% and it has been validated experimentally.
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1. Introduction

3D printing is an advanced manufacturing technology that fabricates parts layer by layer deposition using the FDM 3D printer as shown in Fig. 1. The amount of material is controlled by G-codes using slicing software. FDM is one of the most important 3D printing technology in which parts are build using thermoplastic filaments. The filaments are generally having a circular cross-section with 1.75 mm diameters. FDM fabricates the consolidated parts having complex shapes that reduce the number of assembly units [1]. FDM reduces the lead time along with transportation and storage which help in the supply chain [2]. In traditional manufacturing, the part is shaped by either plastic deformation or subtractive processes like turning, milling, grinding, etc. But rapid prototyping, production is additive or generative. Fused Deposition Modeling uses the polymer material to print the 3d layers of the product. In FDM 3d printing filament is heated in the hot end in a semi-liquid form that comes out through the nozzle (0.4 mm) and ejected on the bedplate on the previous layer. The most commonly used materials are Polylactic Acid (PLA), Nylon, PETG and ABS. The International Organization for Standardization (ISO)/American Society for Testing and Materials (ASTM) defines Additive manufacturing, informally known as three-dimensional printing, as "process of adding the material layer by layer to form 3D parts, as a resist to traditional manufacturing and developmental manufacturing techniques" [3]. Diversity in medical instills from Computed Tomography-imaged tendon replicas have the heedfulness of those in the medical field [4]. Not only in the medical field, but this technology is also effectively used in the construction field. A huddle of houses was printed in bulk quantity by WinSun in China within 24 h [5]. This technology is getting the attention of the automotive sector because of the intricate designs and personalization of certain car parts [6]. Fused deposition modeling is the economical technique of additive manufacturing, which is used for making the working prototypes of thermoplastic polymer/composites [7–12]. The vital drawback of this technology is the top layer roughness, which relies upon the printer minimal thickness [13].

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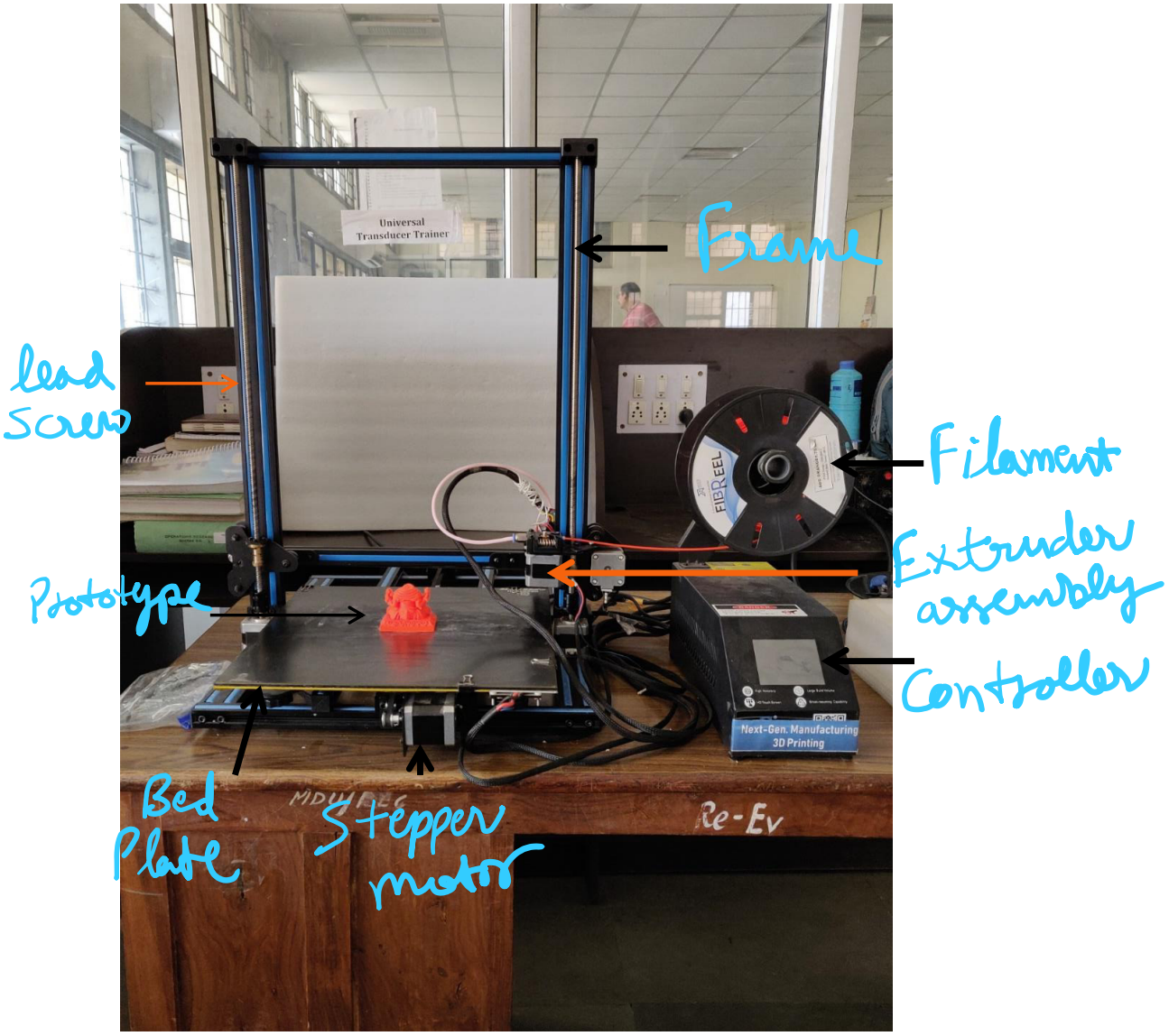

Fig. 1. FDM 3D printer.

Though, many have already been able to reduce the surface roughness through pre-processing and post-processing techniques. Despite, the fact we cannot entirely dispose of surface roughness, most researchers have tested various parameter levels and modifying the slicing technique to minimize the defect [14]. Multi-material 3D printing caters rapid and vigorous structures with a wide range of capabilities of whole combined materials [15,16]. It was recommended that higher dimensional precision, enhanced surface properties, and least post-processing can fulfill by the composite manufacturing (subtraction + addition) [17]. Multi-material three-dimensional printing is germane to the new four-dimensional structure which can render a wide range of capabilities/properties/particular shape [18]. While printing the three-dimensional print the building layers, forgery criterion, combine volatile can influence the conjunction in between the many-sided links [19,20] so these must make, perfect for first-rate automated, Thermal, and other features [21]. Wright et al. [22] have characterized the properties of ABS, uses the design expert tool and discovers that the air void and raster orientation have a substantial impact on tensile strength. Pregger et al. [23] have tested the ABS fabricated solid models in 5 different layer orientations and studied the effect on tensile strength, modulus of rupture, and impact resistance. They found out that ultimate and yield strength was maximum in the 0° orientation and descending in 45/0°, 45/−45°, 90° orientations. Weak interlayer porosity and interlayer bonding were dependent on the layer orientation. The three-point bending test and Izod impact test indicates the highest value in 0° orientation and descending in 45/−45° orientation which caused in weak interlayer porosity and interlayer bonding. Chang and Huang [24] have examined the extruding apertures and profile error for FDM parts. They have fabricated 19 cylinders laid on the contour of the part to evaluate the profile error and to measure the aperture, the designed image of the region was used. They have concluded the parametric design after applying Taguchi's method. Raster angle, part raster width, contour depth, and contour width, these parameters were analyzed in the experiment. As a result, they have concluded that in the FDM process, choosing these parametric criteria could get adequate performances on profile error and extruding apertures. Chhabra et al. [25] used multilevel optimization and Kumar et al. [26] used GA-ANN &

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GA-ANFIS [27] to optimize various process parameters. Deswal et al. [28] optimized the significant process parameter of FDM 3d printer parts to increase their dimensional accuracy using the hybrid tool.

Although a lot of work was published on process parameters optimization for FDM 3D printing using a single material, a few researchers consider the effect of extrusion temperature, infill density and material density for multi-material. This work set up a novel approach to optimize the mechanical properties of FDM fabricated parts using single material and multi-material and by varying infill density, material density and extrusion temperature as process parameters. Hybrid GA-ANN is used to optimize and validate the results.

2. Methodology

The test pieces of different materials like ABS, PETG, and Multi-material were designed in PTC Cero 1.0 software and fabricated with the use of the FDM 3d printer. These test pieces were tested on UTM for tensile strength and the essential process parameters were optimized and validated using a hybrid GA-ANN tool.

2.1. Experimental work

ASTM D638 Type IV standards having thickness (T) 4 mm, a radius of the outer part (RO) of the specimen is taken 25 mm, and whereas the radius (R) of the curved part is taken as 14 mm. The distance (D) between the grips is 65 mm with a gage length (G) of the specimen is 25 mm and the overall length (LO) and the overall width (WO) of the specimen are taken as 115 mm and 19 mm respectively which is shown in Fig. 2. Test pieces were prepared in the PTC Cero software and converted into an STL file. CURA 4.1.0 software, which is used for slicing the STL file and save it into GCODE format. GCODE file fed to the 3d printing machine with the help of either a memory card or a pen drive. For the fabrication of the workpiece, a 0.1 mm gap is maintained between the nozzle and the build plate. The layer height (0.2 mm), wall thickness (1.8 mm), infill pattern (Grid) have been fixed while printing. For a smoother surface, we enable the ironing, in which nozzle goes over the final surface one more time without extruding the filament. The printing speed was 70–80 mm/s for both the filaments. The test piece for each material i.e. ABS, PTEG, and Multi-material are fabricated by depositing material layer by layer. All the movements are controlled by the various stepper motors as per the control program. For the manufacturing of a multi-material workpiece, half part of the test piece is built by using ABS filament and the other half is fabricated using PETG filament.

30 test pieces having magnitude 115 mm length, 19 mm width, and 4 mm thickness was fabricated on the GEEETECH A30 fused deposition modeling machine using ABS and PETG thermoplastic. The FDM test pieces were fabricated using three parameters infill density (20%–60%), material density (1.07 g/cm^3 (ABS), 1.27 g/cm^3 (PETG), 1.17 g/cm^3 (ABS + PETG) and temperature (210 °C–240 °C).

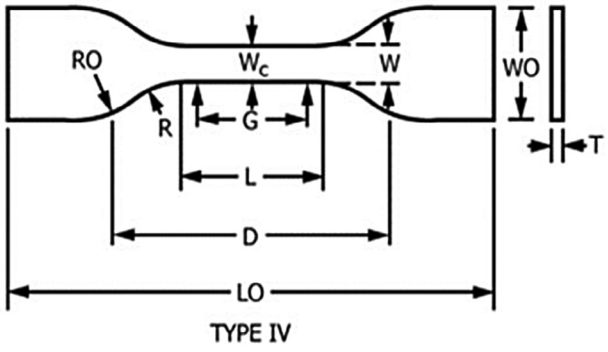

Fig. 2. Type IV test piece.

2.2. Test setup

The electromechanical universal testing machine is utilized to test the mechanical properties of materials like tensile strength, shear strength, and compressive strength. Here, a total of 30 readings were taken as shown in table 1 to establish a test setup for testing the tensile strength of 3d fabricated test pieces of different materials i.e. ABS, PETG, and Multi-material. The custom fixtures were installed to load the test piece in Universal Testing Machine (UTM), all the test pieces were tested at room temperature. Test pieces were tested on UNITEK 94,100 UTM as in Fig. 3.

2.3. GA-ANN modeling

A basic genetic algorithm (GA) uses the random population within the specified range of input parameters to evaluate the given objective function. Further, the genetic algorithm incorporates the mutation and cross over function to produce new offspring for getting greater fitness as elite. Using table 1 data, the ANN model has been trained between input and output parameters and further GA has been applied to maximize the output. The input matrix (30×3) and output data (30×1) have been imported in the neural fitting tool as shown in Fig. 4. The tangent sigmoid activation function has been used for each layer and feed-forward backpropagation network has been created. 70% sample has been used for training, 15% sample for testing and 15% sample for cross-validation. Testing does not bear any impact on training. The value of the correlation coefficient concludes the relationship,

Table 1
Experimental data for UTM.

Material (density)	Infill density %	Temperature °C	Tensile strength kN/mm^2
ABS (1.07 g/cm^3)	20	210	0.027
ABS	22	215	0.027
ABS	25	218	0.028
ABS	30	220	0.028
ABS	35	222	0.029
ABS	40	225	0.03
ABS	45	228	0.029
ABS	50	230	0.028
ABS	55	235	0.028
ABS	60	240	0.027
PETG (1.27 g/cm^3)	20	210	0.036
PETG	22	215	0.04
PETG	25	218	0.041
PETG	30	220	0.038
PETG	35	222	0.04
PETG	40	225	0.044
PETG	45	228	0.036
PETG	50	230	0.037
PETG	55	235	0.04
PETG	60	240	0.041
Multi-material (1.17 g/cm^3)	20	210	0.023
Multi-material	22	215	0.025
Multi-material	25	218	0.028
Multi-material	30	220	0.03
Multi-material	35	222	0.031
Multi-material	40	225	0.032
Multi-material	45	228	0.031
Multi-material	50	230	0.033
Multi-material	55	235	0.027
Multi-material	60	240	0.024

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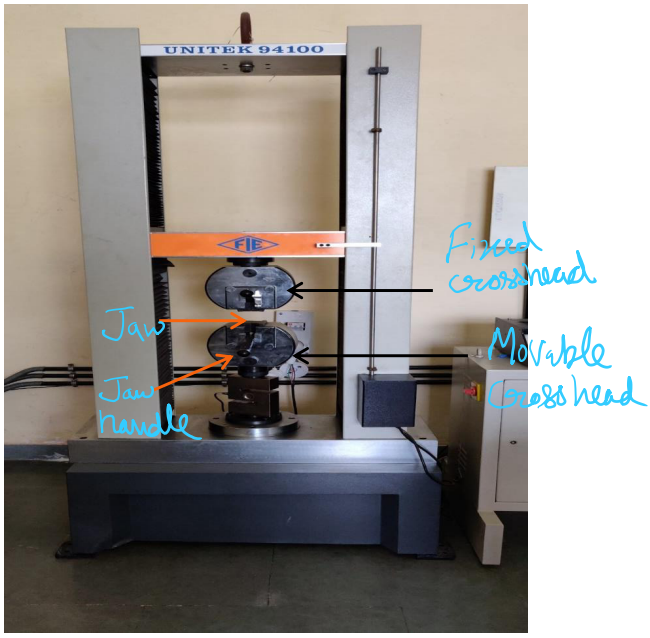

Fig. 3. UTM testing machine.

if it is 0 then it is random and if it is 1 then it is a closed relationship. Further, the ANN model is considered as an objective function in GA to form hybrid GA-ANN. GA by default minimizes the objective function. So, to maximize the tensile strength/objective function, the output of the ANN model is taken as negative. The range of three input parameters infill density, material density, and temperature are defined in GA with lower bound [1.07 g/cm^3 20% 210 °C] and upper bound [1.27 g/cm^3 60% 240 °C] respectively.

3. Result and discussion

The test pieces were prepared using the FDM 3D printing machine using different process parameters and tested for tensile strength on UTM. Process parameters were optimized to maximize the tensile strength using hybrid GA-ANN.

3.1. Tensile strength result and analysis

The tensile strength of thirty 3D printed fabricated test pieces were tested on the UTM and recorded in table 1. It is observed from the table 1 that different materials have various tensile strength at diverse temperature and infill density like ABS is having 0.030 kN/mm^2 tensile strength at 40% infill density and 225° C temperature as shown in Fig. 5, PETG is having 0.044 kN/mm^2 tensile

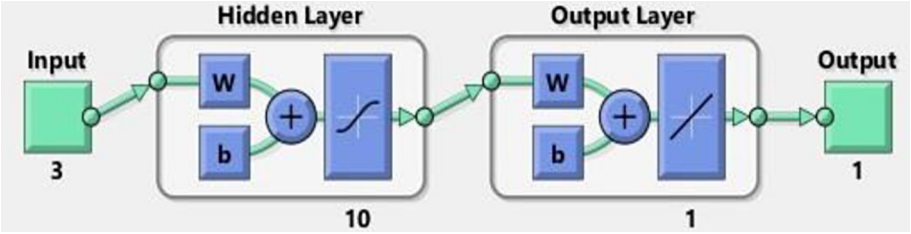

Fig. 4. Artificial neural network.

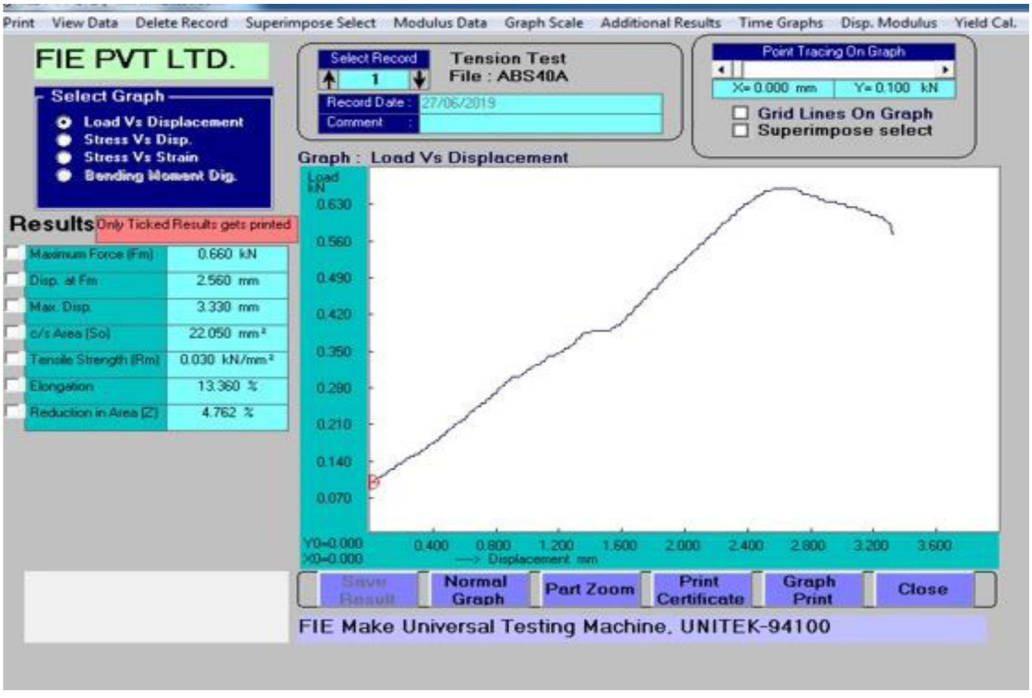

Fig. 5. Tensile strength for ABS at 40 % infill density.

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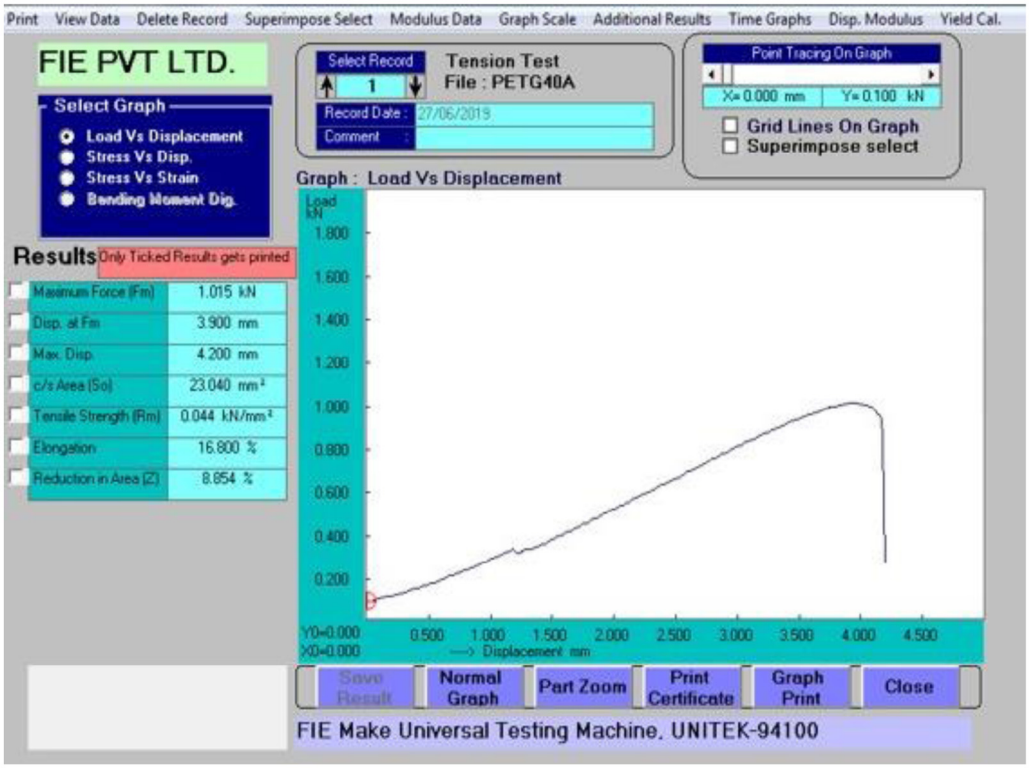

Fig. 6. Tensile strength test for PETG at 40% infill density.

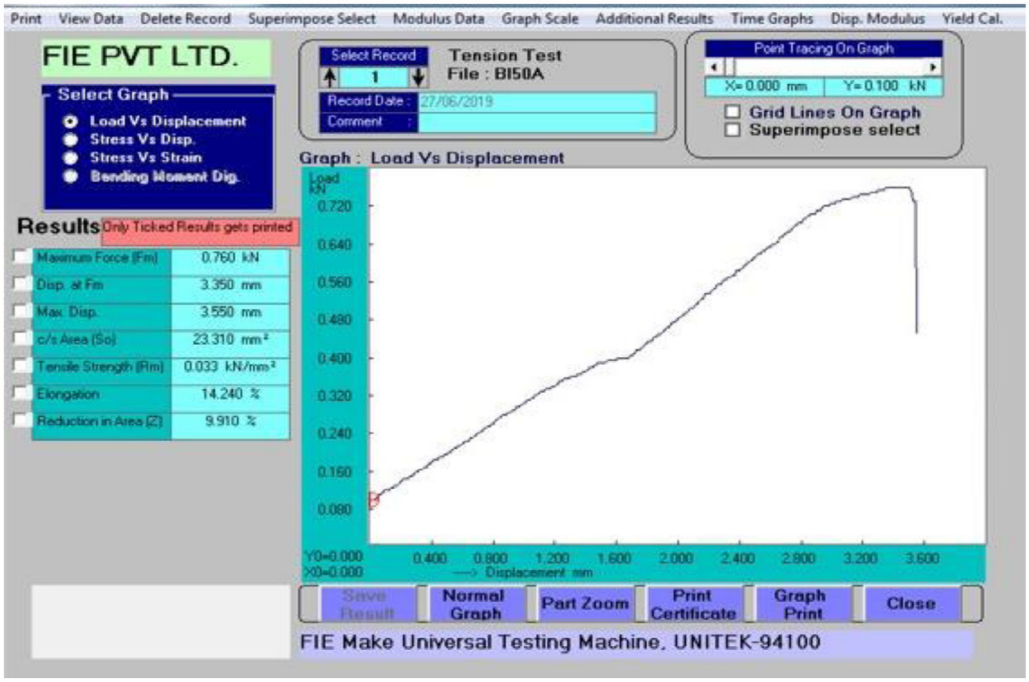

Fig. 7. Tensile strength test for Multi-material at 50% infill density.

strength at 40% infill density and 225° C temperature as shown in Fig. 6, whereas Multi-material is having tensile strength 0.033 kN/mm^2 at 50% infill density and 230 °C temperature as shown in Fig. 7. The Test Pieces which are tested on UTM for tensile strength are shown in Fig. 10.

The tensile strength test is performed for every test piece using the universal testing machine and the averaged results are tabulated in Table 2 and Table 3 for different materials like ABS, PETG, and Multi-Material respectively. Mechanical properties are adversely affected by both the parameters as shown in Fig. 8 and

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Table 2
Tensile Strength of various materials at different infill density.

Sr.no.	Infill Density %	Tensile Strength ABS N/mm^2	Tensile Strength PETG N/mm^2	Tensile Strength Multi-material N/mm^2
1	20	27	36	23
2	30	28	38	30
3	40	30	44	32
4	50	28	37	33
5	60	27	41	24

Table 3
Tensile Strength of various materials at different Extrusion Temperature.

Sr. no.	Temperature °C	Tensile strength ABS N/mm^2	Tensile strength PETG N/mm^2	Tensile strength multi-material N/mm^2
1	210	27	36	23
2	220	28	38	30
3	225	30	44	32
4	230	28	37	33
5	240	27	41	24

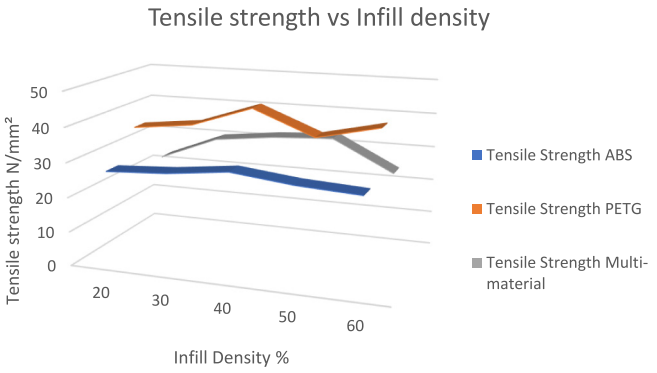

Fig. 8. Tensile strength vs infill density plot for different test pieces.

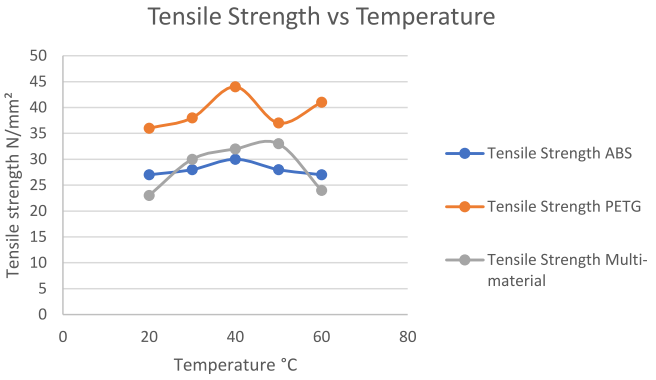

Fig. 9. Tensile strength vs temperature plot for different test pieces.

in Fig. 9. As infill density increase up to 40 percent along with temperature tensile strength of the test pieces of ABS and PETG goes on increasing, beyond the 40 percent the tensile strength starts decreasing even after increasing the extruder temperature. But in the case of Multi-materials, the maximum tensile strength is achieved at 50 percent infill density as shown in Fig. 8. The consequence of the change in extrusion temperature over tensile strength is shown in Fig. 9 for all the materials. We observe that up to a certain limit the tensile strength of the test piece is increased and beyond that temperature limit it starts decreasing as shown in Fig. 9, which is explained by the improved fusion within the extruded layer and between the layers.

The artificial neural network has been trained with 30 sets of three input process parameters (infill density, material density, and temperature) and output response (tensile strength). The best value of overall R (0.97) has been obtained by using the Levenberg-Marquardt algorithm as shown in Fig. 11. This algorithm needed extra memory but lesser time. While training, the data reaches its maximum optimal solution at 7th iteration and when validation samples MSE start increasing, the epochs automatically stop as

Fig. 10. Tested test pieces.

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indicated in the mean square error plot in Fig. 12. The best validation performance obtained is 6.0438e-06 at epoch 7.

The parameters of GA are selected as the population size: 200, elite count: 0.05xpopulation size, crossover fraction: 0.8, crossover function: two-point cross over, mutation function: uniform mutation, and stopping criteria: 200 generations. By taking all these parameters the maximum tensile strength is obtained as 0.046 KN/mm^2 when input parameters are attained as 1.27 g/cm^3 density, 45% infill density, and 239.86 °C temperature and convergence of the best fitness in GA-ANN plot as shown in Fig. 13.

3.2. Validation of ANN-GA model

To validate the hybrid GA-ANN model, 3 parts, one from each material was manufactured by selecting parametric optimization to confirm the forecasted parts. For the same infill density and the temperature, the percentage error associated with diverse test pieces is 2.59%, 2.5%, and 2.6% for ABS, PETG, and Multi-Material respectively as shown in Table 4.

4. Conclusions

This work investigates the influence of infill density, material density, and extrusion temperature on the mechanical properties of FDM printed parts using different materials. The analysis shows that the tensile strength is affected by extrusion temperature and infill density in an identical way. Tensile strength is more influenced by extrusion temperature rather than infill density; higher extrusion temperature favors the high tensile strength of the test pieces up to a certain limit. The maximum tensile strength 44 N/mm^2 is observed in PETG material at an extrusion temperature of 225 °C at 40% infill density in experimental work. The hybrid GA-ANN tool maximizes the tensile strength of PETG to 46 N/mm^2 at 45% infill density and 240 °C temperature which is further validated experimentally.

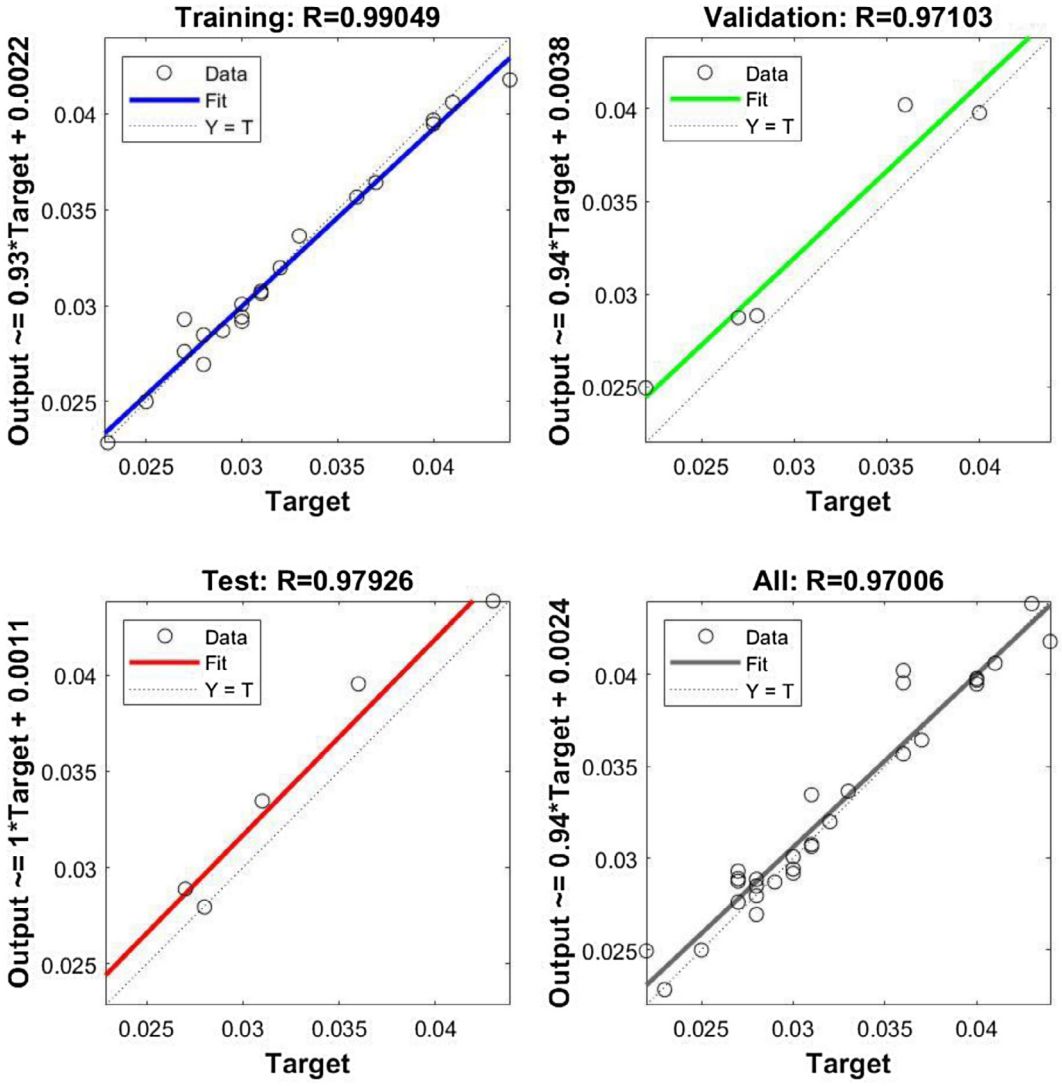

Fig. 11. Regression plot of ANN.

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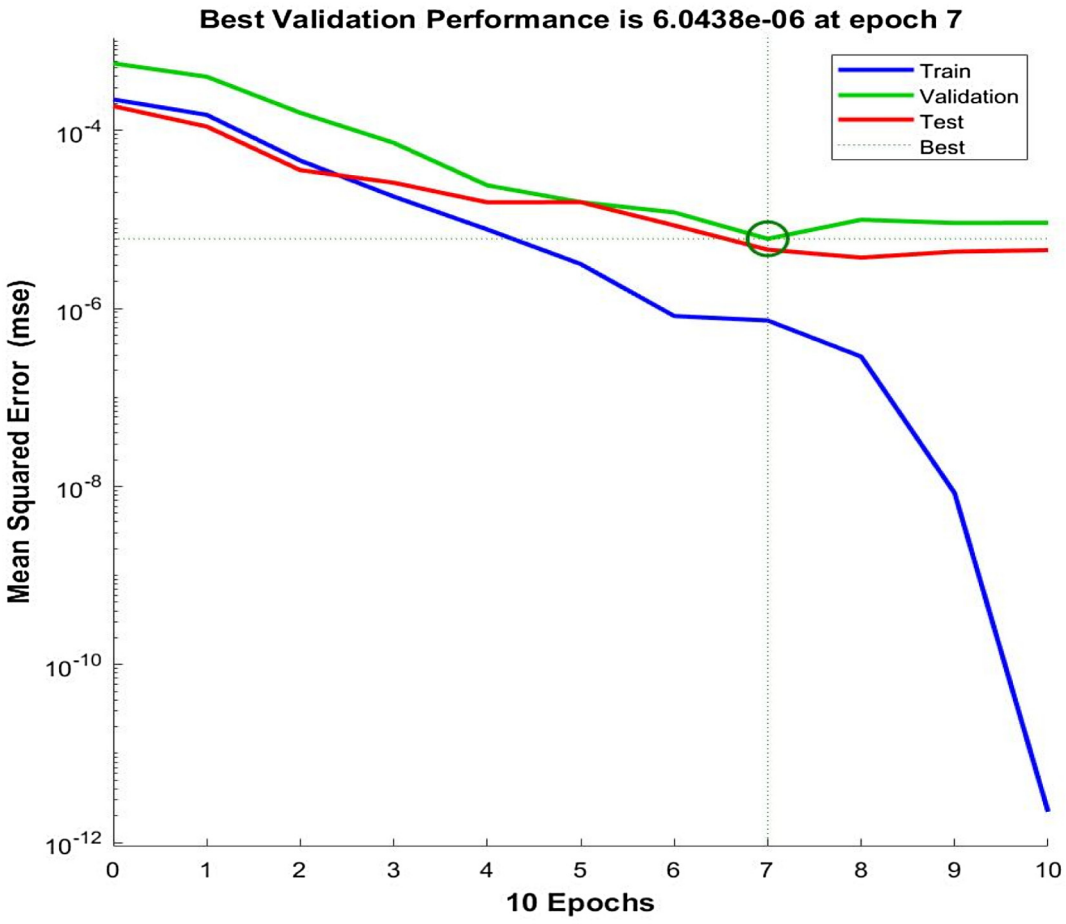

Fig. 12. Mean square error plot.

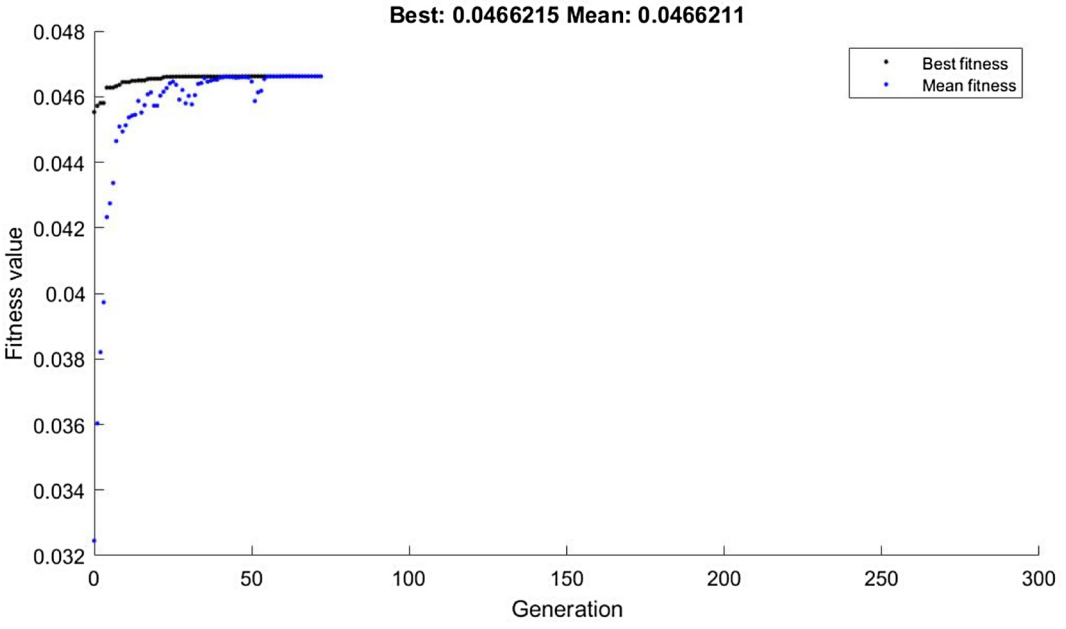

Fig. 13. Convergence of hybrid GA-ANN.

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Table 4
Validation data of GA-ANN Model for different materials.

Sr. no.	Material/density (g/cm^3)	Infill density %	Temperature °C	Tensile Strength as per GA-ANN	Tensile Strength as per experiment	Percentage error
1	ABS (1.07)	20	210	26.3	27	2.59
2	PETG (1.27)	20	210	35.1	36	2.5
3	Multi-material (1.17)	20	210	22.4	23	2.6

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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